A Statistical Approach to Distributed Edge Sensor Detection

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ABSTRACT

Edge sensor detection is often used in identifying regions that are affected by various factors in wireless sensor networks. A statistical methodology based on distributed detection theory and the Neyman-Pearson criterion is developed for edge sensor detection in this research. The input sensor statistics are assumed to be identically independently distributed in our framework. Edge regions and sensors are determined using a hypothesis test, where the observation model for each hypothesis is derived. A sub-optimal distributed detection scheme, which is optimal among detectors having the same test at all local sensors, and the way of choosing the optimal operating point are described. The condition under which the proposed scheme outperforms the optimum detector based on a single sensor is presented. Furthermore, the noisy channel effect is considered, and a method to overcome this noisy effect is addressed. The performance of the proposed distributed edge sensor detection scheme is studied via computer simulation, where the ROC curves are used to demonstrate the tradeoff between the cost (in terms of the sensor density) and detection accuracy.

Keywords: e dge sensor detection, sensor network, distributed detection, Nyeman-Pearson criterion

1. INTRODUCTION

Research on sensor networks has drawn much attention recently [1,2]. Environmental monitoring, military surveillance, and monitoring of manufacturing facilities are examples of the wide provisional application of sensor networks. In such a network, a large number of low-cost sensors powered by batteries are randomly deployed in the area to be monitored. Since the communication and computation capability of each sensor is limited, the efficient usage of these resources is one of main challenges in the sensor network design and deployment. Wireless inter-sensor communication is typically assumed. Energy and communication bandwidth limitation demands localized and distributed processing of data [1-6]. It is apparent that successful applications heavily rely on the networking capability. The ad-hoc connectivity, energy efficient medium access control, routing, transportation, synchronization and localization techniques are characteristics of senor networks. By assuming that these networking capabilities are ready, we focus on one specific application of sensor networks in this research, *i.e.* edge sensor detection.

Detection, classification and tracking of targets are major applications of sensor networks [2,3]. In some applications, the target is not a point but appears as an area. For example, we may monitor a forest area caught on fire or an area polluted by chemical or biological material. We may need to decide the affected area as exactly as possible for evacuation or deployment of counter actions. Effective edge detection is needed for this type of applications.

Quite a few edge detection methods have been developed in image processing. Since readings by sensors located on fields being monitored can be viewed as images, those edge detection algorithms may be borrowed and used in the context of sensor networks. However, there are some differences in these two application contexts. Image pixels are located in a regular pattern with an uniform density while sensors are distributed irregularly with non-uniform density. Conventional edge detection in image processing relies on the calculation of 1st and/or 2nd order derivatives. This is however not allowed in sensor networks due to the irregular pattern. Hence, edge detection algorithms for sensor networks need to be tailored. We have to pay attention to distributed data processing among sensors with limited communication capability.

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Internet Quality of Service, Mohammed Atiquzzaman, Mahbub Hassan, Editors,
Proceedings of SPIE Vol. 5245 (2003) © 2003 SPIE · 0277-786X/03/$15.00

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The rest of this paper is organized as follows. Related previous work is reviewed in Section 2. The edge region is defined and the observation models are described in Section 3. The optimal fusion scheme with all sensors having the same test is developed in Section 4. Performance analysis is carried out and the way to determine the optimal operating point is presented in Section 5. We take channel errors into consideration in Section 6. Experimental results are shown in Section 7. Finally, concluding remarks are given in Section 8.

2. PREVIOUS WORK

In this section, we review some previous work and discuss its relationship with our current work. Nowak and Mitra [5] proposed an edge approximation method for sensor networks using recursive dyadic partition (RDP). Chintalapudi and Govindan [6] presented a statistical classifier-based approach to edge sensor detection using filtering. While a hierarchical network architecture was assumed and utilized in [5], there was no hierarchy among sensors in [6]. Another major difference between them is that the real boundary was approximated in [5] while the edge sensor was detected in [6]. Both [5] and [6] demand a large amount of inter-node cooperation and communication. Among the two, the communication requirement in [6] is slightly lower, which has an advantage in sensor networks. The sensor reading in [6] was assumed to be a simple binary outcome. This model is however too simple to allow more complicated processing and enhanced detection performance. No optimality was attempted in [6]. This shortcoming can be overcome by introducing a distributed detection scheme, where sensor readings are statistically described so that the optimal processing is feasible in local sensors and the fusion center.

In this research, we detect edge sensors as defined in [6] by following a distributed detection approach. Distributed detection theory has been developed since early 80's [7]. Rather than making decision based on a single sensor reading, local decisions of scattered sensors are gathered at the central node, where the final decision is made. The central node is typically called the fusion center, and the operation of integrating local decisions to form the final decision is called fusion. As will be discussed in Section 3, an edge sensor is determined by sensors surrounding itself and, consequently, the problem itself asks for distributed detection. Optimal distributed detection was derived under the Bayesian criterion in [9] and the Neyman-Pearson criterion in [8]. Since a priori distribution is generally not known in edge sensor detection, the Neyman-Pearson approach is adopted in this paper. There was no closed form for the optimum solution to the distributed Neyman-Pearson detection problem given in [8], where the optimal operating points for sensors were found numerically. In this work, we present a distributed detection scheme, where all sensors have the same test for their local decisions and the fusion rule is optimized. Hence, the proposed scheme is optimal among that class of detectors. The advantage of our scheme over the one given in [8] is that we obtain a simple closed-form solution for the optimal operating point. Also, the condition under which the proposed scheme outperforms the detector based on a single sensor reading is derived.

In distributed detection of edge sensors, every sensor plays the role of a fusion center to decide whether it is in the edge region or not. At the same time, it also serves as a surrounding sensor for its neighboring sensors to facilitate their decision making. The hypotheses made on edge sensors are dependent on certain local measurements and, as a result, the hypotheses structure is different from that of the conventional centralized decision problem. The proposed scheme removes the position dependence caused by irregular sensor locations by averaging the position-dependent pdf's over the space. It is also assumed that measurements at sensors are independent, and the same statistical models are used at all sensors for decision making. Inter-sensor communication is restricted to a single bit. The distributed edge sensor detection system will be detailed in the next section.

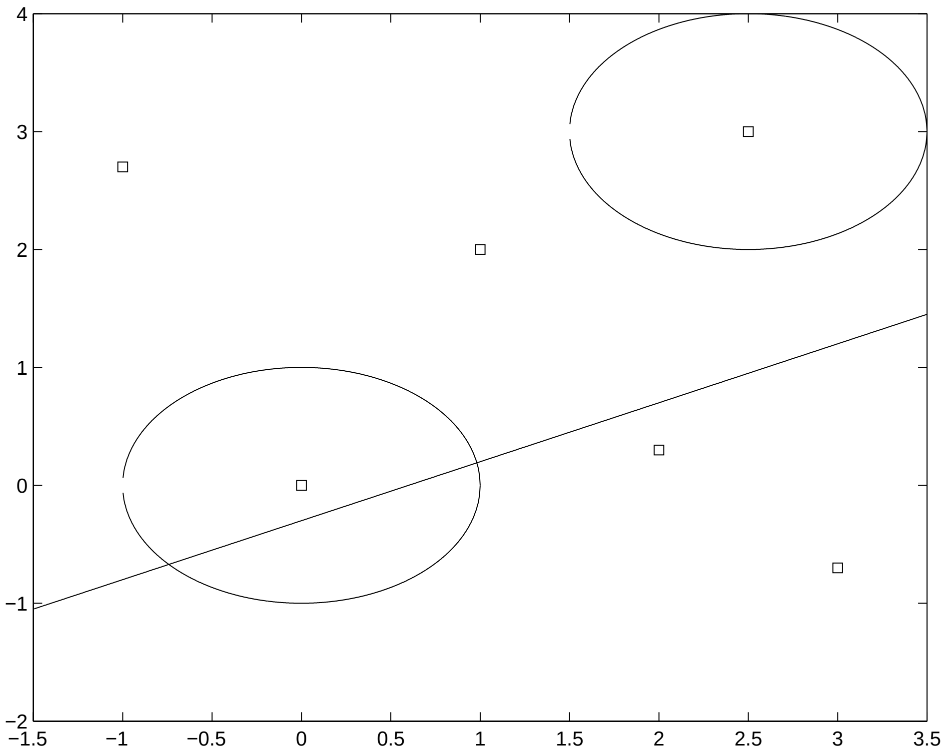

Figure 1. Illustration of an edge and sensors around the edge.

3. EDGE REGION AND OBSERVATION MODEL

In the context of image processing, pixels are positioned regularly and an edge is typically approximated by connected line segments of a single pixel width. Since sensors are distributed in an irregular pattern in the sensor network, it is not easy to find a thin edge. Instead, as done in [6], we will detect an edge region that has a certain width called the tolerance range. We show the plot of sensors and a line edge in Fig. 1, where squares represent sensor locations and the radius of the tolerance range is set to r. To give an application example, in the monitoring of wild fire, one possible scenario is that the region above the edge is on fire while the region below the edge is not.

The edge region is defined to be the region whose distance from the actual edge is within the tolerance range r. Thus, the width of the edge region is equal to $2r$. Edge sensors are sensors located within this region. In Fig. 1, sensor at(2.5,3) is not an edge sensor while sensor at (0,0) is. The sensor reading is characterized by a probability function $p_1(x)$ for the phenomenon-exiting area (*e.g.* on fire) and another probability function $p_0(x)$ for the phenomenon-non-exiting area (*e.g.* not on fire). For the illustrative purpose, let us assume $p_0(x) = g(0, \sigma^2)$ and $p_1(x) = g(1, \sigma^2)$, where $g(i, \sigma^2)$ is the Gaussian distribution with mean i and variance σ^2. Now, let us consider the following scenario. We would like to decide if a sensor is in the edge region or not, and there are n sensors within the tolerance range of the sensor. These n sensors will participate in the decision by sending their local readings to the sensor in question, where the decision fusion will be made.

Let hypothesis H_1 denote the case that the sensor is an edge sensor while hypothesis H_0 denote the case that it is not. Here, we assume that the decision whether a sensor is in the phenomenon region or not is already made accurately, and our goal is to find out the edge sensors which are located in the region of phenomenon*.

*It is possible to include types of error probabilities in deciding whether sensors are in the problem area or not. However, this generalization will make the derivation afterward quite complicated and prevent us from focusing on the edge sensor

For each sensor belonging to the n neighboring sensors, the sensor reading statistics under each hypotheses are given as

$$\begin{aligned} P(x|H_0) &= g(1,\sigma) \\ P(x|H_1) &= g(0,\sigma)/8 + 7g(1,\sigma)/8 \end{aligned} \tag{1}$$

The value of $P(x|H_1)$ can be justified by the following arguments. As shown in Fig. 1, the circle around sensor B is the tolerance range of B. The area outside of the region affected by the phenomenon is

$$r^2 cos^{-1}(\frac{l}{r}) - l\sqrt{r^2 - l^2}, \tag{2}$$

where l is the distance between the sensor B and the real edge. The probability of the distance l under hypotheses H_1 is $p(l|l < r) = \frac{2l}{r^2}$. By averaging (2) over the distribution of l, we end up with $\pi r^2/8$. Thus, the average area outside the region of phenomenon under H_1 is $1/8$ of the total tolerance range. Of course, this is zero under H_0. From the viewpoint of sensors in the tolerance range of B, they are located arbitrarily in the space and the probability for them to fall outside of the problem area is $1/8$ and the remaining probability goes to inside of the area. Thus, we obtain (1).

The above derivation is based on the line edge assumption. Although edges in the real-world situation are likely to be of various shapes, the line edge nevertheless provides a good approximation to real-world edges if the tolerance range is relatively small, and edges do not change their orientation in a short distance. The likelihood ratio at each sensor is given by

$$\Lambda(x_i) = \frac{P(x|H_1)}{P(x|H_0)} = \lambda(x_i)/8 + 7/8, \tag{3}$$

where $\lambda(x_i) = g(0,\sigma^2)/g(1,\sigma^2)$. Note that if $\lambda(x_i)$ is a monotonically decreasing function of x_i, $\Lambda(x_i)$ is also a monotonically decreasing function of x_i.

4. OPTIMAL FUSION RULE

4.1. The Case without the Communication Constraint

Before addressing distributed detection where local sensors make their own decisions and send them to the fusion center, let us consider the following case first: there is no communication constraint at all so that local sensors are able to send the unprocessed readings to the fusion center for final decision. This scheme will provide a benchmark for the performance of the distributed detection scheme. Let $x = [x_1, \ldots, x_n]^n$. Following (3), the likelihood ratio of x is given by

$$\Lambda_n(x) = \prod_{i=1}^{n} [\lambda(x_i)/8 + 7/8]. \tag{4}$$

It is difficult to find the sufficient statistics from (4). Here, we use a heuristic statistics $x = \sum_{i=1}^{n} x_i$, which results in a suboptimal decision. Then, the observation models for x are

$$\begin{aligned} P(x|H_0) &= g(n, \frac{\sigma^2}{n}) \\ P(x|H_1) &= \sum_{i=0}^{n-1} \begin{pmatrix} n \\ i \end{pmatrix} \frac{7^i}{8^n} g(i, \frac{\sigma^2}{n}). \end{aligned} \tag{5}$$

We can apply the Neyman-Pearson detector directly to x and find the Receiver Operating Characteristic (ROC) from distributions given by (5).

detection problem. Thus, perfect decision is assumed available for sensors in or out of the region of phenomenon.

4.2. Optimal Fusion Rule

In this subsection, we will develop the optimal fusion rule when the same decision rule is applied to local sensors. Let $u = [u_1, u_2, \ldots, u_n]$, where $u_i \in [0, 1]$ is the decision at the ith sensor and $C = \{u|f_n(u) = 1\}$, where $f_n(\cdot)$ is the fusion function. Let $P(u|H_0)$ and $P(u|H_1)$ be probability of u under hypotheses H_0 and H_1, respectively.

The Neyman-Pearson detector minimizes the probability of missed detection ($i.e.$ $P_M = 1 - P_D$) while keeping the probability of false alarm P_{FA} less than a certain threshold denoted by α. Thus, the objective function is

$$F = P_M + \beta(P_{FA} - \alpha) = \sum_{u \in C} [\beta P(u|H_0) - P(u|H_1)] + 1 - \beta\alpha, \tag{6}$$

where β is the Lagrangian multiplier. For specific u^*, (6) can be rearranged as

$$F = \beta P(u^*|H_0) - P(u^*|H_1) + \sum_{u \in C - u^*} [\beta P(u|H_0) - P(u|H_1)] + 1 - \beta\alpha. \tag{7}$$

The optimal fusion rule is derived from (7) as

$$f_n(u^*) = \left(\begin{array}{ll} 1 & \text{if } P(u^*|H_1) \geq \beta P(u^*|H_0), \\ 0 & \text{otherwise} \end{array} \right. \tag{8}$$

The optimal fusion rule turns out to be the likelihood ratio test of u.

Here, we assume that the readings of all sensors are independently and identically distributed according to distributions given by (1). All sensors make decision with an identical test so that each sensor has the same local probability of detection (p_d) and false alarm (p_f)[†]. At the fusion center with n surrounding sensors, the probability of observing k local H_1 decisions under each hypotheses is

$$\begin{aligned} P(k|H_0, n) &= \binom{n}{k} p_f^k (1 - p_f)^{n-k}, \\ P(k|H_1, n) &= \binom{n}{k} p_d^k (1 - p_d)^{n-k}. \end{aligned} \tag{9}$$

Hence, the likelihood ratio of observing k of H_1 local decisions is

$$\Lambda_n(k) = \frac{P(k|H_1, n)}{P(k|H_0, n)} = \frac{p_d^k (1 - p_d)^{n-k}}{p_f^k (1 - p_f)^{n-k}}. \tag{10}$$

Note $k = \omega(u)$, where $\omega(x)$ returns the weight of binary vector x. We can show that (10) is a monotonically increasing function of k via

$$\begin{aligned} & \frac{p_d^k (1 - p_d)^{n-k}}{p_f^k (1 - p_f)^{n-k}} - \frac{p_d^{k+1} (1 - p_d)^{n-k-1}}{p_f^{k+1} (1 - p_f)^{n-k-1}} \\ = \quad & \frac{p_d^k (1 - p_d)^{n-k-1} (p_f - p_d)}{p_f^{k+1} (1 - p_f)^{n-k}} \leq 0. \end{aligned} \tag{11}$$

In (11), we assume $p_d \geq p_f$ in all distributions and likelihood based detections. Hence, the optimal decision can be obtained by thresholding on k,

[†]Since $\lambda(x_i)$ is a monotonically decreasing function, $p_d = \int_{-\infty}^{s} p(x|H_1)dx, p_f = \int_{-\infty}^{s} p(x|H_0)dx$, where s will be found in Section 5.

$$P_{FA,n} = \sum_{k=t}^{n} \left(\begin{array}{c} n \\ k \end{array} \right) p_f^k (1-p_f)^{n-k},$$
$$P_{D,n} = \sum_{k=t}^{n} \left(\begin{array}{c} n \\ k \end{array} \right) p_d^k (1-p_d)^{n-k}, \tag{12}$$

where t is a threshold value on k. Note that t in

(12) can take integer $1, 2, \cdots, n$.

5. PERFORMANCE AND OPTIMAL OPERATING POINT

We showed the optimal detection strategy among the class of detectors in Section 4, where all local sensors have the same test. One can take the threshold on $k = \omega(u)$, and there are n possible candidates for the optimal fusion, *i.e.* $t = 1, 2, \cdots, n$. In this section, we derive a method to select the optimal fusion rule and a test for local sensors satisfying the Neyman-Pearson constraint (*i.e.* $P_{FA,n} = \alpha$). As a byproduct, we will identify the condition under which the proposed distributed detection scheme outperforms the detector based on a single sensor's reading.

For each t, we have $P_{FA,t} = f_{t,n}(p_f)$ and $P_{D,t} = f_{t,n}(p_d)$, where

$$f_{t,n}(x) = \sum_{k=t}^{n} \left(\begin{array}{c} n \\ k \end{array} \right) x^k (1-x)^{n-k}, \quad 0 \le x \le 1. \tag{13}$$

For the example of $n = 2$, we have $f_{1,2}(x) = 2x - x^2$ and $f_{2,2}(x) = x^2$. Let $p_d = R(p_f)$ be the ROC curve relation produced by the likelihood detection of the single sensor reading and given by (1). From the Neyman-Pearson constraint, we have

$$\begin{aligned} P_{FA,t} &= f_{t,n}(p_{f,t}) = \alpha, \\ p_{f,t} &= f_{t,n}^{-1}(\alpha), \\ P_{D,t} &= f_{t,n} R f_{t,n}^{-1}(\alpha). \end{aligned} \tag{14}$$

From (14), we can identify $p_{f,t}$ and $P_{D,t}$ for each t [‡]. Among $P_{D,1}, P_{D,2}, \cdots, P_{D,n}$, the one with the largest value gives the optimal fusion rule (t^*) and the associated local test (s_{t^*}). Hence, the optimal detectior finds t^* such that

$$t^* = arg \max_t f_{t,n} R f_{t,n}^{-1}(\alpha). \tag{15}$$

It is not guaranteed that the performance of the proposed scheme is always better than that of the detector based on a single sensor's reading. From (14), we see that if $R(x) = f_{t,n}(x)$, then the tth fusion function has the same performance as that of the one based on a single sensor's reading.

Fig. 2 shows cases for $n = 2$. When $R(x) = x^{1/\mu}$, the fusion function $f_{2,2}(x)$ has the same performance as that of a single sensor detector. The difference $f_{t,2} R f_{t,2}^{-1}(\alpha) - R(\alpha)$ in Fig. 2(a) reveals that the optimal fusion will choose $t = 1$ for any values of $p_{FA} = \alpha$. When $R(x) = 2x - x^2$, the fusion function $f_{1,2}(x)$ has the same performance as that of the single sensor detector. The difference $f_{2,2} R f_{2,2}^{-1}(\alpha) - R(\alpha)$ in Fig. 2(b) indicates that the proposed detector is not better than the one with a single sensor reading. Another curve in Fig. 2(b) is for the case $R(x) = f_{1,3}(x) = 3x - 3x^2 + x^3$ and $f_{1,2}(x)$. We see that the difference is negligible.

[‡]The function s_t is found by $\int_{-\infty}^{s_t} p(x|H_0)dx = p_{f,t}$

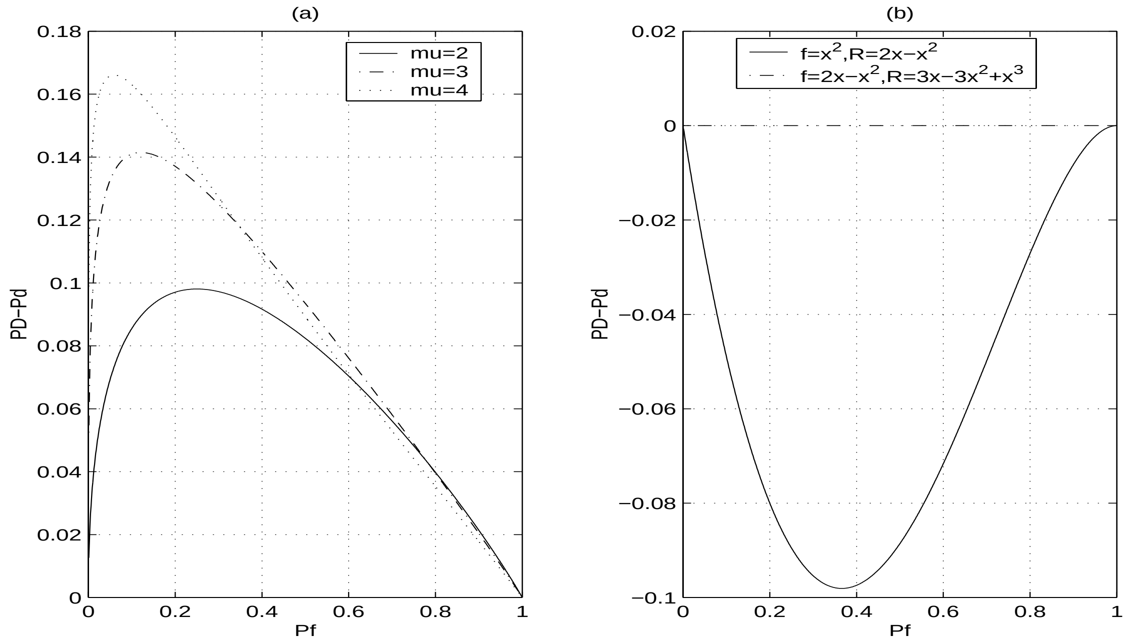

Figure 2. The plot of $f_{t,2}Rf_{t,2}^{-1}(\alpha) - R(\alpha)$:(a) t=1, $R(x) = x^{1/\mu}$ and (b) t=2, $R(x) = 2x - x^2$.

The condition for the proposed detector to outperform the one based on the single sensor reading in performance can be written as

$$f_{t^*,n}Rf_{t^*,n}^{-1}(\alpha) \geq R(\alpha). \tag{16}$$

We abandon the proposed distributed detection scheme and make decision based upon only one sensor reading, *i.e.* take an arbitrary local decision when the condition in (16) is violated for all t.

Fig. 3(a), (b) and (c) provide the ROC curves of the proposed distributed detection (DD) scheme when the input distributions are described by (1) and $n = 2, 3, 4$, respectively. The ROC's of the one with a single sensor decision (Orig.) and the one based on observation models in (5) (no constraint) are also shown in Fig. 3(d) for comparison. Note that the statistics in (5) is not optimal, hence the curves with no constraint are below those of the proposed scheme when $n = 3, 4$. Also, we see that the performance grows with an increase of n for the given case.

6. EFFECT OF CHANNEL ERRORS

In this section, we will discuss the modification of the proposed method when inter-sensor communication is corrupted by channel errors with a known probability. The binary symmetric channel with the cross-over probability p_e is adopted. In this case, the probabilities of false alarm and detection at each local sensor are modified to be

$$\begin{aligned} p'_f &= (1-p_e)P(u_i = 1|H_0) + p_e(1 - P(u_i = 1|H_0)) = (1-2p_e)p_f + p_e = g(p_f) \\ p'_d &= (1-p_e)P(u_i = 1|H_1) + p_e(1 - P(u_i = 1|H_1)) = (1-2p_e)p_d + p_e = g(p_d), \end{aligned} \tag{17}$$

where $g(x) = (1-2p_e)x + p_e$. Since $p_d = R(p_f)$, we have $p'_d = gRg^{-1}(p'_f)$. Thus, R is effectively changed to gRg^{-1}. Note that the transform of $R(\cdot)$ by g moves (0,0) and (1,1) to (p_e,p_e) and ($1-p_e$,$1-p_e$), respectively.

If p_e is known to the system, the system will work with gRg^{-1} instead of R. Thus, the system will find the fusion rule via

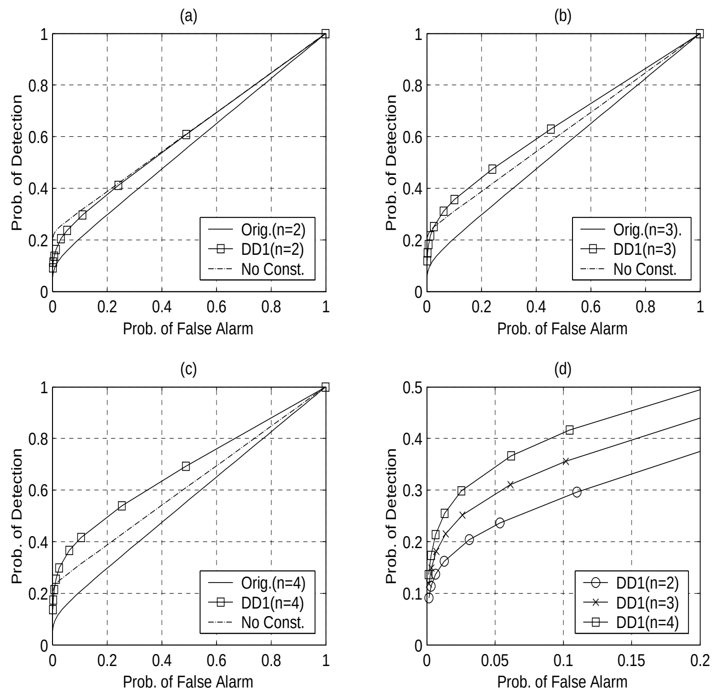

Figure 3. The ROC curves: (a) n=2, (b) n=3, (c) n=4, (d) comparison between n = 2,3 and 4.

$$t^* = arg \max_t f_{t,n} g R g^{-1} f_{t,n}^{-1}(\alpha). \tag{18}$$

In this case, not all the value of α in (0,1) is reachable. The minimum value is $f_{n,n}(p_e) = p_e^n$ and the maximum value is $f_{1,n}(1 - p_e)$.

When the system does not know p_e, it will work with R. The probability of false alarm will be $fgf^{-1}(\alpha) \neq ff^{-1}(\alpha) = \alpha$ and the fusion rule is not guaranteed to be optimal.

7. SIMULATION RESULTS

The simulation environment is shown in Fig.4. The area with the phenomenon of interest is above $y = 0.4$ while the are below this line is not affected by the phenomenon. Hence, we are simulating the line edge case in this example. The tolerance range is set to 0.2, and the area surrounded by $y = 0.4$ and $y = 0.6$ is the edge area, and sensors in this area are edge sensors. Positions marked with 'x' are sensor positions and those marked with 'o' are decided to be edge sensors by the distributed detection algorithm. We see one missed sensor in the edge area and no false alarms in the area with $y > 0.6$.

The statistical results are plotted in Fig. 5. As discussed in Section 5, the detection performance depends on the number of sensors in the tolerance range, which is Poisson distributed with the parameter of the sensor density. Three sensor density cases are compared, *i.e.* $\rho = 0.2, 0.3, 0.45$ in the unit area of 0.1 x 0.1, and the signal-to-noise ratio is equal to 9dB. It happens that certain unit areas have no sensors in the tolerance range. In this case, we can take random decision with a false alarm rate (α). The results are averaged over 800 realizations with respect to an area of 1 by 1, where there are 20, 30 and 45 sensors in this area according to the density. Even though the false alarm and the detection probability probabilities are rather high (between 0.05 and 1), a large number of simulations is essential since the observation models are spaciously averaged and the sensor distribution is statistical.

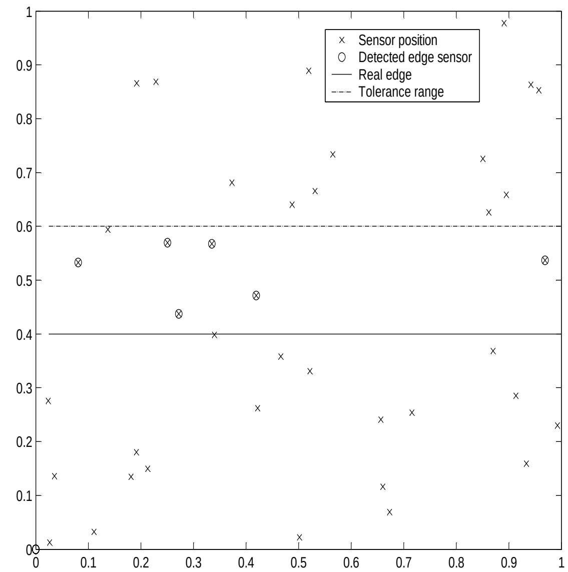

Figure 4. The simulation environment.

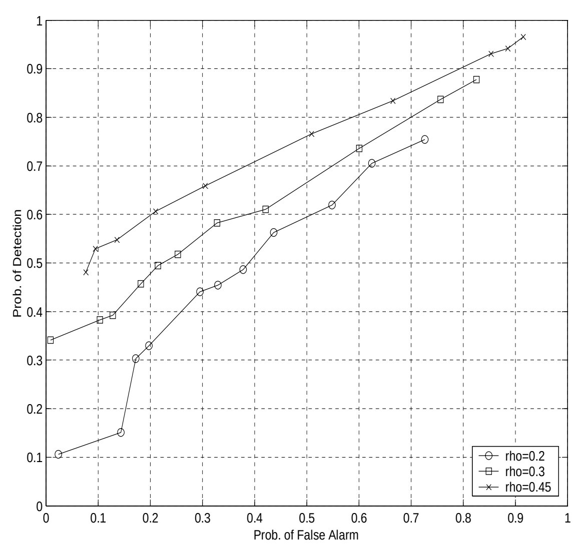

Figure 5. The simulated ROC performance.

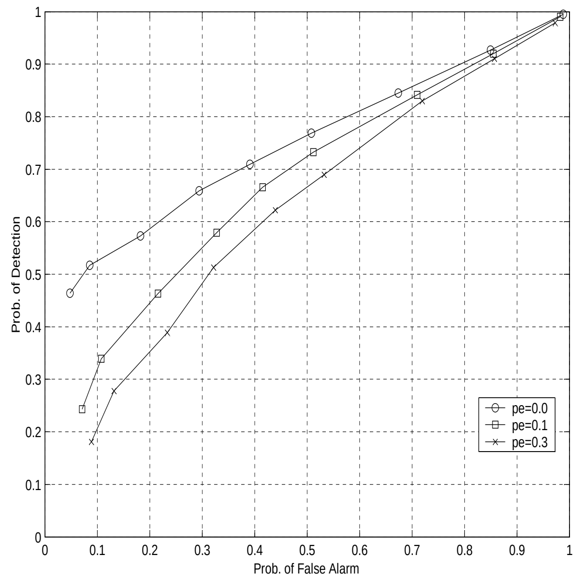

Figure 6. The ROC performance when there are channel errors.

As expected, as the density increases, we have better results. This is due to the tradeoff between the cost (*i.e.* the number of sensors) and the performance. Also, we see a noticeable difference at the low false alarm rate than the high false alarm rate, which is the rate of the highest interest. We assume that the decision of each sensor on the edge will be sent to a remote console, where the final decision will be made by human eyes considering geometrical distribution of decisions. It is anticipated that the demanded false alarm rate for edge detection is not as high as in target detection for radar or sonar applications. Further improvement in performance can be obtained by adopting more dense quantization of sensor readings, which will increase inter-node communication, which will be consider in our future work.

Fig. 6 shows the system ROC performance for error rates are equal to 0, 0.1, 0.3, respectively. Since sensor networks are typically operating in the wireless mode with a limited power and simple circuitry, the assumption of a relatively high error rate seems natural. The SNR is set to 9dB and the density of sensors per unit area(0.1x0.1) to set to 0.4. We see that the performance degrades as channel errors increase and we need to adopt the method proposed in Section 6.

In Fig. 7, we compare the ROC performance of the system with and without the knowledge of the channel error rate. At a high false alarm probability, there is no difference in ROC's. In the low false alarm rate case, we see a larger range of the unreachable false alarm probability if the system does not know p_e. This is because that the system without the information of p_e thinks all the fusion rules are available for these low false alarm probabilities, and may chooses among those fusion rules. However, in reality, only some part of fusion rules is available at low and high probability regions. (Depending on ROC's, this can also happen in the high probability region.) In this experiment, the system selects $f_{1,n}(\cdot)$ or $f_{2,n}(\cdot)$ most of the time, and fails to reach the low probability region. Note that the minimum of $P_{FA,k}$ is $f_{k,n}(p_e)$ and its maximum is $f_{k,n}(1-p_e)$.

Note that, for the system that does not know p_e, it does not have the ability to control the false alarm probability as explained in Section (6).

8. CONCLUSION AND FUTURE WORK

A distributed detection scheme was presented and applied to edge sensor detection in the sensor network in this research. The Neyman-Pearson criterion was adopted to optimize the detector and all local sensors were assumed to have the same test. The optimal fusion rule was identified as threshold on the weighting of local decisions,

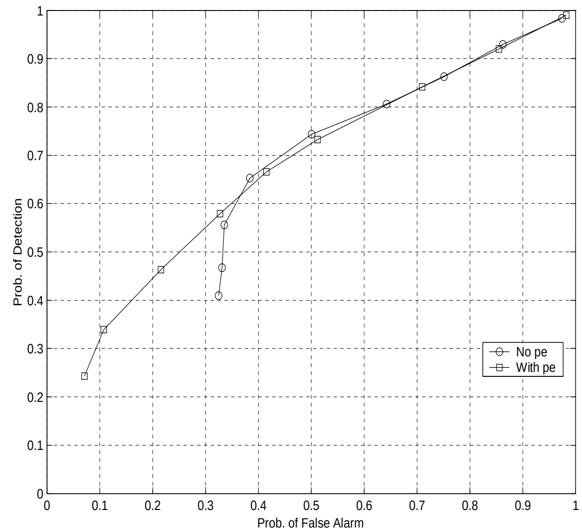

Figure 7. The ROC peformance with and without the knowledge of p_e.

and the operating point at each sensor was determined through the constraint and the function between the false alarm probability of local sensors and that of the overall system. The condition under which the proposed scheme outperforms the single sensor reading was identified with illustrative examples, where we showed that the proposed scheme may not always outperform the single sensor detector. Given the channel error rate, a method to deal with channel errors was proposed. Simulation results showed a trade-off between the cost (*i.e.* the number of sensors) and the performance. The channel error can be handled effectively if the cross-over probability is known. When the cross-over probability is not known, the system may not reach the low or the high probability of false alarm depending on distributions. More experimental comparison will be carried out to compare the proposed distributed detection scheme with other existing methods in the near future.

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